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Investigatory Brain-Computer Interface utilizing a single EEG sensor

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Investigatory Brain-Computer Interface utilizing a single EEG sensor

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REPORT

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Investigatory Brain-Computer Interface utilizing a single EEG sensor

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A Human-Machine Interface is a device that allows humans to interact with and use machines. One such device is a Brain-Computer Interface which allows the user to communicate to a computer system through thought patterns. A commonly used technique, electroencephalography, uses multiple sensors positioned on the subject's cranium to extract electrical changes as a representation of thought patterns. This report investigates the use of a single EEG sensor as a user-friendly BCI implementation. The primary goal of this report is to determine if specific mental tasks can be reliably detected with such a system.

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Chapter 1

Introduction

Since the development of the personal computer, human-machine interaction (HMI) has become a relevant research area. A specific type of HMI is the brain-computer interface (BCI) which aims to control a computer system with the brain activity of the user. Historically, the driving factor for BCI applications is to enable persons suffering from physical ailments and to improve quality of life for those individuals. However, BCI systems are not developed exclusively for handicapped individuals.

Recently, additional research has targeted commercial product offerings and enabling researchers through easing the difficulties of data capture. Thus the 'computer' in BCI is usually not a traditional personal computer and often is some sort of specialized computer system. This could be an application specific system such as a mobility aid [1], an embedded microcontroller, or merely a research development system.

The current research in this area can provide BCIs for handicapped and healthy individuals that have achieved moderate to high success rates [1]. These systems have several types of implementations such as Near-Infrared Spectroscopy (NIS) [2], Electroencephalography (EEG) [3], functional Magnetic Resonance Imaging (fMRI) [4], and Steady State Visual Evoked Potential (SSVEP) [5]. Additionally, there is BCI research that involves invasive surgical techniques, but these systems and techniques are beyond the scope of this research. The focus will remain primarily on EEG except where it is necessary to compare other methodologies.

1.1 BCI Techniques

One of the primary obstacles to effective BCI systems is the accompanying hardware require for a functional BCI implementation. Each of the aforementioned BCI techniques require specific hardware at varying levels of inconvenience to the user.

For example, fMRI requires the subject to remain motionless within an MRI machine while under observation which obviously limits the potential applications for such a system. Functional MRI systems provide high spatial resolution and thus are commonly used for detecting activity in specific regions of the brain. This is achieved by detecting the change in blood flow in response to additional oxygen being sent to active regions of the brain [6]. Though fMRI is very capable of detecting brain activity, the hardware limitations typically limit its uses to clinical investigations and patient therapy rather than BCI applications.

Similarly, NIS systems require a device capable of imaging near-infrared light reflected off of the blood vessels in the brain. Both systems operate by detecting localized changes in blood density in captured images and thus require some level of precision imaging and placement with respect to the user. While some compact NIS systems have been developed [7], the systems are still bounded by the hardware required to produce and detect near-infrared light. This results in a cumbersome apparatus not intended for common use.

EEG is perhaps the most popular interface for BCI systems due to its relatively non-invasive nature. EEG relies on voltage potentials measured on the skin's surface caused by electrical activity within the brain. Traditional EEG systems utilize a skullcap designed to hold tens of sensors in specific locations on the scalp. Often times these sensors are coated with a conductive gel in order to increase the signal-to-noise ratio (SNR) as a major issue with EEG systems is low SNR. The preparation and placement of sensors is often a time-consuming process that must be performed by someone other than the user.

One specific technique that utilizes EEG is SSVEP. Typical SSVEP implementations involve a visual stimulus such as a multiple flashing lights at a multiple known frequencies. EEG signals are then captured and monitored for suspected responses in conjunction with the subject observing one or more of the specific frequencies. This type of system is typically custom designed to determine if the subject is observing a predetermined area of a computer screen that has an established output or meaning depending on the context of the experiment. The nature of these systems, while effective and more in-line with common interactions with computer systems, is dependent on the pre-determined meaning associated with the user intentionally observing one of the flashing sectors. This ultimately limits the meaningful implementations of SSVEP.

1.2 EEG Implementation

In essence, BCI systems are pattern recognition systems that function on the patterns of observed brain activity. In order to establish and identify patterns from the raw EEG electrical signals, certain features of the signals are identified and monitored. In this research, the BCIs are trained with supervised learning wherein features are fed to the BCI with their known correct output. In this manner the BCI can learn how to appropriately classify inputs and test itself to determine its own accuracy.

Feature selection, as well as feature extraction, is an important aspect of BCI development. Due to the indirect nature of EEG signals from brain activity, the features extracted are an abstraction of the true brain activity. As such different EEG features have their respective strengths and weaknesses. Common features include signal amplitude, band power, power spectral density, autoregressive parameters, time-frequency features, and inverse model-based features [8]. Features alone only represent a recreation of the EEG signals, a dataset that must be fed through a classifier or classifiers for the actual pattern recognition. Thus the classifier selection also is an important aspect of BCI development. Often times there are multiple classifiers used either in parallel or cascaded to combat classification biases or to process different types of features. The most popular classifiers are linear classifiers and neural network classifiers.

1.3 Report Outline

This research aims to advance the current state-of-the-art further by successfully detecting mental tasks with a single dry EEG sensor. Progress in this direction would enable new interactions between humans and computers without the need for cumbersome peripherals. This is especially relevant in an age where computer systems are migrating away from traditional personal computers towards smaller personal electronics. By investigating feature extraction within the context of a limited dataset, this research avoids the curse of dimensionality and focuses on generating a user-friendly, functional offline BCI system.

In the following chapters, current state of the art will be discussed in Chapter 2, the project design of this research in Chapter 3, project implementation in Chapter 4, results of this research in Chapter 5, and conclusions in Chapter 6.

Chapter 2

Prior Art

The development of EEG BCI systems typically involves the following process: data capture, feature extraction, offline processing, and online processing. In the following sections each of these topics are discussed in more detail.

2.1 Data Capture

The process of data acquisition can be considered two separate design decisions, sensor location and capture methodology.

2.1.1 Sensor Location

Typically EEG data is recorded with as many channels or sensor locations as possible in order to avoid a lack of data. Then channels can be excluded from use if the data complexity proves to great. The *de facto* standard for sensor location is the International 10-20 (Figure 3.1) system which uses 21 locations though some researchers choose to measure intermediary locations as well. The various regions of the human brain are responsible for differing functions. By recording all channels, researchers hope to avoid any loss of data due to the underlying brain function. For example, “the frontal lobe is concerned with reasoning, parts of speech and movement, emotions, and problem-solving” whereas “the temporal lobe is concerned with hearing and memory” [9]. Thus for detecting a mental task such as arithmetic, sensors over the frontal lobe would likely yield more relevant data than signals over the temporal lobe. Another interesting aspect is that sensors over the occipital lobe (which is primarily concerened with vision) would likely vary largely depending on whether or not the subjects’ eyes are open during the recording.

2.1.2 Capture Methodology

Capture methodology refers to the process the subject undergoes in order to obtain brain activity data. Often this involved some sort of auditory or visual cue to perform some mental task. This cue occurs at a known point in time that can be correlated to the data in offline processing of the separate mental tasks. It is necessary to record a baseline mental task where the subject is not performing any mental activity in order to distinguish other tasks from the norm. The other mental tasks requested are typically specific to the BCI application and vary from study to study.

For the mobility aid BCI in [1], the subject was given visual cues from a computer monitor to alternate between two mental tasks, relaxation and kinesthetic motor imagery (KMI). This was performed over the course of 10 minutes in 30 second intervals. This process provides a large window of data associated with both mental tasks.

In other studies like [10] by Faradji *et al.* the data may actually be acquired from other research groups. In this case from [11] where data was acquired for five different mental tasks with 10s capture intervals. This process was repeated five times to constitute a session, and each subject recorded two different sessions. This particular study, as with many others, recorded measurements both with eyes open and eyes closed. By recording data with the eyes closed, artifacts introduced from the subject blinking are avoided; it also allows the subject to focus on the task at hand without distractions from visual stimuli.

2.2 Feature Extraction

The extraction of features is performed offline as this allows researchers to develop and test the BCI without the subject. It also allows the researchers to revisit which features they choose to extract as this process can be done repeatedly after the data acquisition. The most common features are as follows:

- Signal Amplitude: Signal voltage for some associated time period.
- Band Power: Brain waves are commonly divided into frequency bands associated with specific mental tasks (see Table 2.1).
- Power Spectral Density: Distribution of power across the frequency range.
- Autoregressive Coefficients: Coefficients of an autoregressive model.

- External Features: Features that are correlated with EEG data but do not originate from the EEG data.

Table 2.1: EEG Frequency Bands

Name	**Frequency**	**State**
Delta	0.1Hz to 3Hz	Deep, dreamless sleep, non-REM sleep, unconscious
Theta	4Hz to 7Hz	Intuitive, creative, recall, fantasy, imaginary, dream
Alpha	8Hz to 12Hz	Relaxed, but not drowsy, tranquil, conscious
Low Beta	12Hz to 15Hz	Formerly SMR, relaxed yet focused, integrated
Midrange Beta	16Hz to 20Hz	Thinking, aware of self & surroundings
High Beta	21Hz to 30Hz	Alertness, agitation

Often the BCI application will dictate which types of features are chosen. For example, where a gross attentiveness value is the desired output, a power calculation for the upper Beta spectrum would be appropriate, but this would not be discernable using signal amplitude at a given time. However, when detecting ocular artifacts, peaks in signal amplitude are often a key feature used to identify regions of interest.

Additionally, feature selection rarely ends with one choice as many times there are varying means of representing the same feature. In the case of Do *et al.*, power spectral densities where broken down into two hertz bins. There is no published indication in [1], but this value was likely tested at multiple intervals and concluded to perform best at two. Similarly, Faradji *et al.* indicate that the AR model order they use varies not only from subject to subject but also from task to task in order to obtain the highest performance from each customized BCI.

2.3 Offline Processing

As with feature extraction, the offline processing stage of development is performed iteratively on the data collected and may involve the addition or revision of the extracted features. The majority of the BCI development process is performed here on tasks such as classifier implementation, evaluating process parameters, and pattern training.

2.3.1 Classifiers

An extensive review of classifiers for EEG BCIs by Lotte *et al.* exists. For our purposes we will briefly summarize their findings beginning with a list of the most common classifiers below.

- Linear Classifier: Discriminate algorithms that use linear functions to distinguish classes, most popular.
- Neural Network Classifier: An assembly of multiple artificial neurons which produce a nonlinear decision, popular.
- Nonlinear Bayesian Classifier: Probabilistic nonlinear discriminating classifier, not widely used.
- Nearest Neighbor Classifier: Distance based algorithms to calculate most likely class, rarely used.

- Combinations of Classifiers: The combined use of multiple classifiers to overcome shortcomings of a single classifier, increasing popularity.

Lotte *et al.* include case examples of each classifier examined. For our case studies, Do's robotic gait orthosis uses a linear Bayesian classifier focused on determining the probability of a feature being in the 'Idle' state versus the 'Walking' state. If the probability of 'Idle' is greater than 'Walking', then the classifier discerns the state must be 'Idle'. In [10] the BCI uses a Quadratic Discriminant Analysis, a type of nonlinear Bayesian classifier, for each mental task individually.

2.3.2 Classification Problems

As indicated, the nature of BCI development involves recording vast amounts of data from subjects and analyzing the data after the recording sessions. This lends to large amounts of data from multiple subjects and multiple sessions, especially considering that researchers may have elected to record 64 separate EEG channels at a time [1]. Then consider the feature extraction; this dataset may enlarge or shrink (though unlikely), possibly resulting in a vast amount of data to process. Researchers are left to develop some means of discovering what data is useful or not. Consider for example the difference between a dataset wherein the peak amplitude is chosen over a given time period versus the dataset wherein the PSD is calculated over 2 Hz increments for the same period of time. This increase of dataset complexity is sometimes referred to as the 'curse of dimensionality' [8]. Without addressing the curse of dimensionality, classifiers may suffer performance degradation or not perform at all. Additionally, the sheer amount of data obscures meaningful feature sets.

Classifiers have a natural trade off between bias and variance, where bias is the divergence between the estimated mapping and best mapping and variance is the sensitivity to the training set. Simple classifiers tend to have high bias and low variance. This means if a simple classifier is capable of learning from the training data despite its low variance, it may suffice in place of a more complex solution. Whereas on the other hand, more complex solutions may have a lower bias, more accurately reflecting the correct classification, but are more sensitive to variations in the training data and may suffer from overtraining.

2.4 Data Sampling

Implied by the list of common features, often times voltage measurements at a single point in time are not sufficient to build a meaningful feature. Thus a decision for how to partition and sample the incoming data is necessary. This has an impact on system complexity, the effectiveness of features, and the overall latency of an online implementation. In order to collect enough consecutive data points, the incoming data stream is often partitioned into segments near one second in length. The segments begin at varying intervals as well. The sample interval is often near or below ¼ second. Theoretically, this allows an online BCI system to respond within one second or less.

2.5 Online Processing

Depending on the stage of development and target application, some research takes an additional step of implementing the BCI designed offline in an online implementation. These are sometimes called ‘self-paced’ BCIs, as the user may control the system at his/her will rather than being instructed when to provide brain input. As seen in [1], the BCI combined with a commercial robotic walking assistant creates the quintessential brain controlled mobility aid. The subject is placed within the mobility aid atop a treadmill and attached to the EEG BCI device. When the subject performs brain activity for KMI, in this case the imagined act of walking, the developed BCI determines probabilistically the subject’s intent to walk and sends control signals to the robotic assistant to initiate motion.

Chapter 3

Project Design

The goal of this research is to investigate a BCI utilizing a single dry EEG sensor capable and determine if it is possible to detect a single mental task whilst striving to minimize FPR and maximize TPR. The driving factor for this research is to increase the usability of EEG BCIs by limiting the available dataset to only that which is obtained in a user-friendly form factor.

The complexity of EEG signal analysis, particularly the low SNR, generally forces BCI implementations to rely on many EEG channels collectively to function. However, this is often cumbersome and impractical from a usability standpoint. Furthermore, research has shown that specific areas of the brain are responsible with specific tasks such as motor control, memory, or comprehension [9]. Accordingly, the EEG signals generated from specific tasks are stronger in close proximity to those areas, and thus specific locations on the cranium are often chosen in accordance to the mental task that is desired. This complicates the concept of a generalized single EEG sensor BCI since the optimal location may or may not have strong SNR for all relevant mental tasks. Figure 3.1 illustrates the location of sensors according to the International 10-20 system, the *de facto* standard for EEG sensor locations

[12]. Since SNR is a large concern, sensors are placed directly on the skin if at all possible. Conductive gel helps sensors that must be located on hair-covered areas. However, since convenience is a design element, the use of wet sensor is considered not feasible for our purposes.

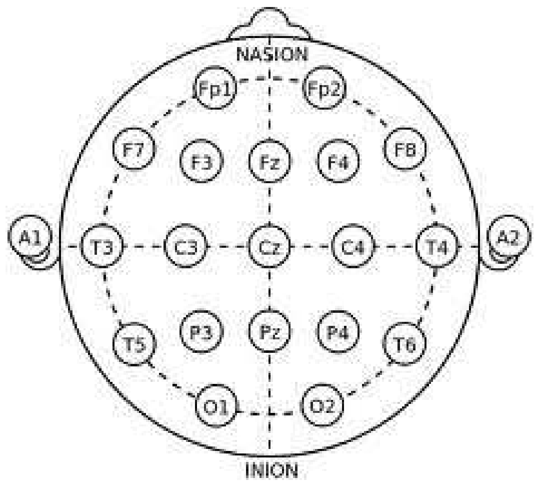

Figure 3.1: International 10-20 Sensor Locations

For the sake of user-convenience this sensor will be located at FP1, which is located off-center on the forehead at 10% of the distance from the naison to the inion. The underlying area of the brain in this case is Brodmann Area 10. This area is believed to be responsible for cognitive functions such as planning future actions and working memory [13]. For the mental tasks chosen in this research (See Table 4.1), this is a reasonable location to measure EEG as tasks such as 3D object rotation involve the formulation of an object in the mind's eye and constant re-evaluation of what is visible versus what is obscured. However, it may be less desirable for KMI as this area has little to do with motor control.

Chapter 4

Project Implementation

As previously mentioned, this research implements a dry single sensor EEG BCI for detecting mental tasks. The development of this BCI is detailed below in similar fashion to the BCIs described in the Prior Art chapter.

4.1 Data Capture

The data capture was performed on the author, a single male test subject, over seven test sessions with two sessions occurring during the same sitting. All sessions were performed in a dim-light, quiet (but not sound controlled) environment. The raw EEG data was collected using a Neurosky MindBand sensor recording at 512 Hz. The MindBand holds a dry EEG sensor and reference node within a headband that can be positioned on the subject's cranium. Internal hardware implements a hardware filter on the range 3Hz to 100Hz and has 12 bits of ADC resolution. The subject received visual instructions and cues from a computer monitor prompting him to perform a preset sequence of mental tasks. The final sequence performed is listed in Table 4.1. The visual cues consisted of large easy-to-read white text on a solid black background. Initially the same sequence was used with task lengths of

30 seconds. However, it was determined that over the course of 30 seconds the subject was not maintaining the mental task for the full duration.

Table 4.1: Mental Tasks Sequence

Time	**Mental Task**
0-10s:	Instructions
10-20s:	Idle Thought
20-30s:	Multiplication
30-40s:	Idle Thought
40-50s:	3D Object Rotation
50-60s:	Idle Thought
60-70s:	Visual Counting
70-80s:	Idle Thought
80-90s:	Kinesthetic Motor Imagery

4.2 Feature Extraction

Throughout the development, multiple features were extracted from the collected data. The full list of features extracted is included below.

- Power per Frequency Band
- Peak Amplitude
- Autoregressive Coefficients
- Blink Occurrence

The performance of these features is discussed in the following chapter.

4.3 Offline Processing

Once the EEG data was recorded, many offline processing steps were performed to increase performance of the BCI. Traditionally, during this process the captured data would undergo some dimensionality reduction technique in order to extract the most meaningful contributors to the output. However, in the case of this research, there is only one sensor data set and any reductions in data are detrimental to BCI performance.

The majority of this process focused on resampling data series. Data points were resampled into a varying length segments ranging from .25 seconds to 1.25 seconds. These samples were taken at a varying intervals ranging from ½ second to 1⁄64 second. This results in an oversampled dataset that, as Faradji [10] indicates, "helps combat the stationary problem of EEG signals." Because each oversample provides the data to extract features for that time period, these design variables were evaluated for multiple feature sets. The performance of the BCI was first measured with each combination of sample length and sample interval in order to determine strong candidates for use. When autoregressive coefficients were used as a feature, the order of the AR model was also varied between 15 and 45 based on prior work [10]. The performance of these variables is discussed in the following chapter.

4.4 Classifier

Based on prior art, it was determined that one or more neural networks would be a strong candidate for use in the developed BCI [8]. These neural networks were implemented in MATLAB using the Neural Network Toolbox. These neural networks used a scaled conjugate backpropagation algorithm for training. The number of internal nodes was also varied between 5 and 15 as the performance of the classifier was measured to determine strong candidates for use.

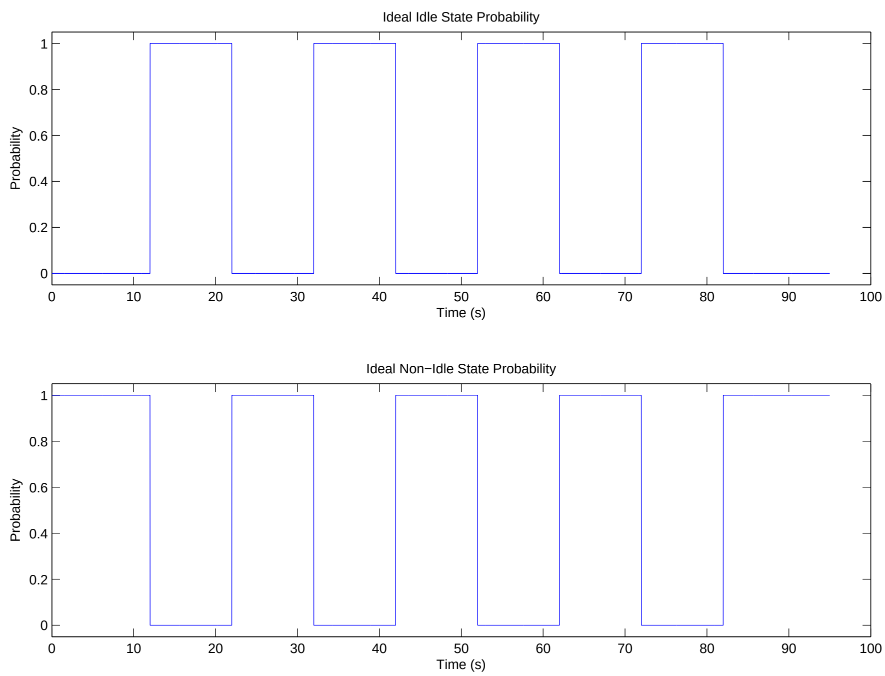

Figure 4.1: Ideal Two State Output

In order to train the neural networks, batches of post-processed data were fed to the neural network. This requires extracting oversampled data from the post-processed data and associating that extracted data with the desired output (based on the time from the original data capture) for the mental tasks under test. Figures 4.1 and 4.2 illustrate the ideal outputs for distinguishing between two mental states and five mental states respectively.

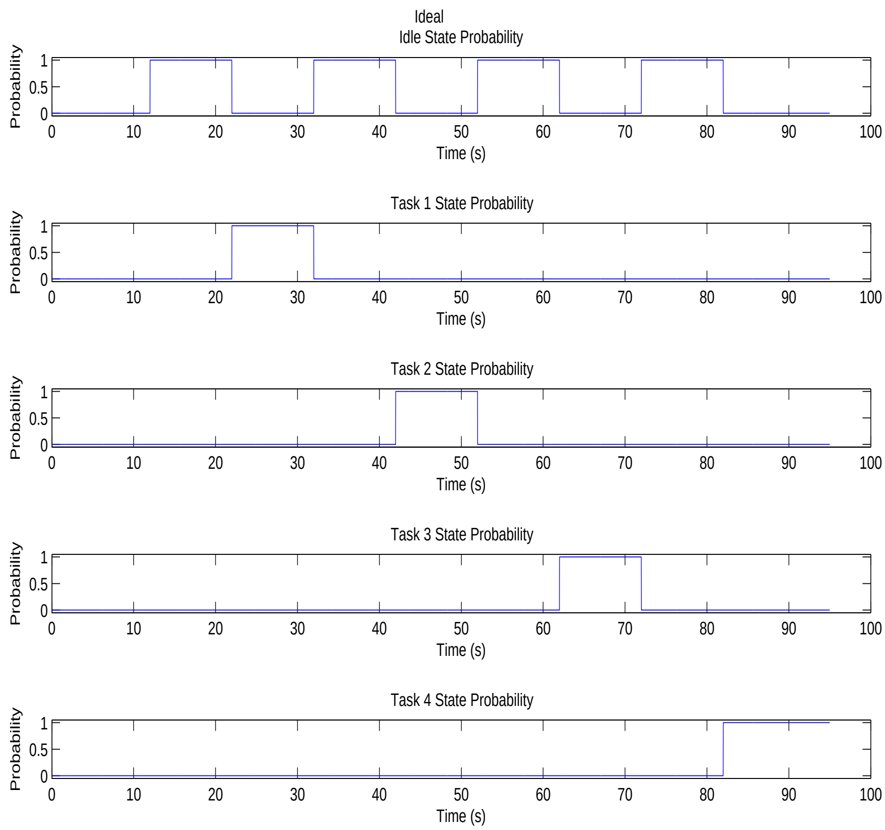

Figure 4.2: Ideal Five State Output

There were two types of post-processed data used, data that originated from an isolated session and data that was combined with data from multiple other sessions. For both single-session data sets and multiple-session data set, seventy-five percent of the data was selected for training, fifteen percent for

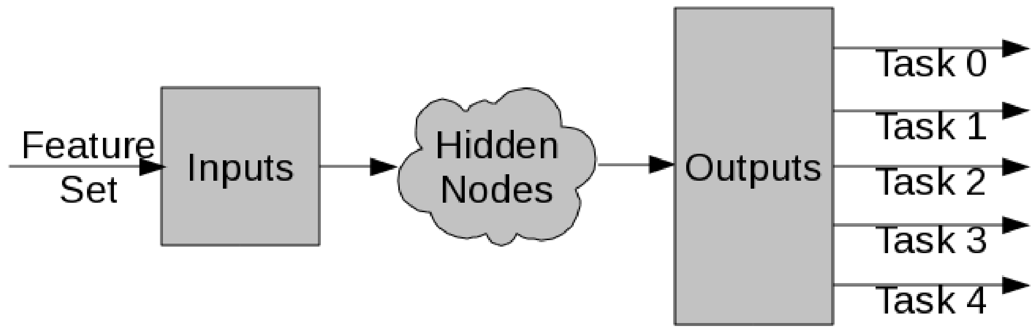

Figure 4.3: Single Neural Network

validation, and fifteen percent for testing. The subsections of data chosen for each task were randomly selected. In cases where the performance of multiple networks was evaluated against each other, the same randomly chosen data was used for all networks under test. In addition to evaluating the performance of the neural network classifiers, the classifiers were tested and utilized in multiple configurations. Two primary configurations were used: one classifier for all output states (Figure 4.3) and one classifier for each output state (Figure 4.4).

4.5 Online Processing

Though many BCIs are developed to process EEG data streams in real time. This proved to be beyond the scope of this project and remains future work for this particular research.

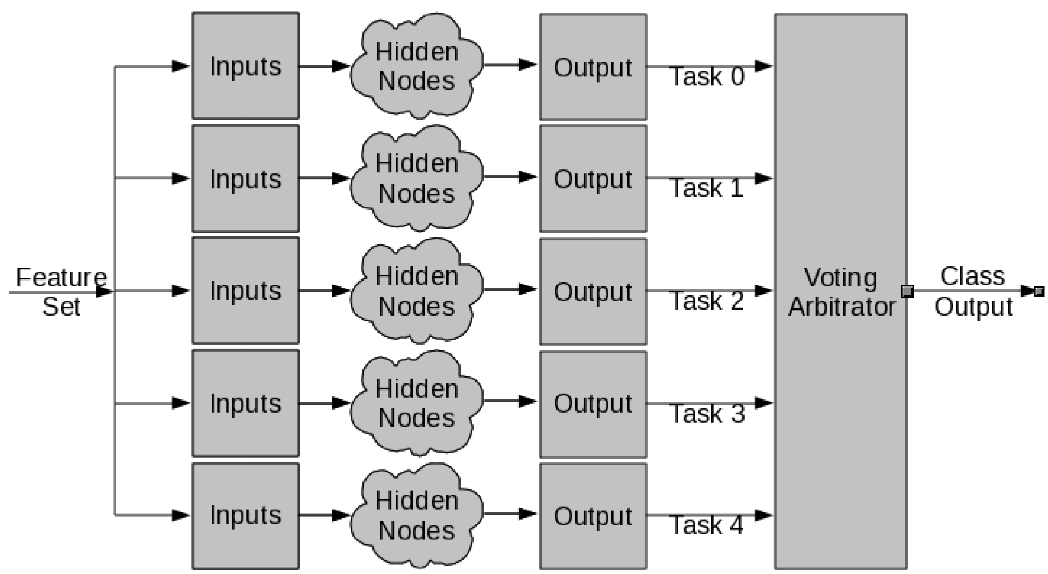

Figure 4.4: Multiple Neural Networks

Chapter 5

Results

There are multiple metrics for evaluating the performance of BCI systems. One metric is to compare the classifier output to the expected output based on the instructed sequence. The ratio of incorrect classifications to total classification is considered a confusion percentage. This is only useful for a single network at a time but was used in our evaluation of feature selection. The other common metric for BCI systems is true positive rate (TPR) and false positive rate (FPR) which were calculated according to formulates (5.1) and (5.2).

$$TPR = \frac{TP}{TP + FN} \tag{5.1}$$

$$FPR = \frac{FP}{samples} \tag{5.2}$$

In the above equations TP is the number of true positives, FN is the number of false negatives, and samples is the total number of samples in the dataset.

Performance metrics will be discussed by considering BCIs utilizing data from a single session and data from multiple sessions. Within these categories both BCIs configured to detect idle versus non-idle and all five mental tasks will be considered. It should be noted that there is notion of uncertainty inherent to BCI systems since there is no decisive indicator that the subject is sufficiently performing the expected mental task. During offline processing, an ideal candidate that consistently performs the requested mental task perfectly over the expected time interval is assumed for performance calculations.

5.1 Preprocessing variables

The preprocessing variables for sample length and sample interval were evaluated using a single neural network and identical randomly selected data from a single session at a time to control reproducibility. The classifier was configured to detect idle versus non-idle mental states. In this manner, the variables were swept across relevant ranges and the resulting confusion was recorded. Utilizing the Pearson's Correlation, between the variables and confusion revealed that longer sample length and lower sample interval both lend to lower confusion percentages.

This is partially agreement with Faradji's finding, "Selecting largely overlapping short segments mitigates the stationary problem of EEG signals" [10]. However, the distinction of 'short' is not entirely clear as samples of one second were used in their BCI. The correlated data from this research indicates that longer samples tend to yield higher performance. However, it was not determined if this eventually becomes untrue as overall system latency was considered for an online implementation, and increasing sample length increases system response time due to more data points being collected prior to classification.

5.2 Feature Performance

From the previous chapter, multiple features were evaluated in order to discover strong candidates for use. Initially, power per frequency band (as described in Table 2.1) was used as the primary feature. This was evaluated at multiple sample lengths, sample intervals, and internal node counts, but results proved to be inconclusive as the confusion percentage for a single network testing for both idle versus non-idle mental states and all five mental tasks varied as low as 16% to as high as 44% but typically fell between 30-40%. This inconsistency held across multiple data sets from different recording sessions.

In addition, a configurable threshold was added to detect peak amplitudes and flag samples that contained a peak as an input to the classifier. The threshold was tested at multiple values of the meaningful range (i.e. sufficiently high to exclude some subset of samples and sufficiently low to not exclude all samples). However, no appreciable increase in performance was measured. These results led to the exclusion of power as an included feature for classification despite its success in prior art.

Instead each oversample was modeled with an autoregressive model calculated using the Burg method [11]. These coefficients were then used as the inputs to the neural network for classification. The network was tested multiple times with similar data and promising results were recorded for longer, more overlapping samples. Again Pearson's Coefficient indicated that sample length and sample interval had more impact on the overall performance of the neural networks than the order of the AR model. This is likely because the AR model range was sufficiently high for all values tested (15-45). For this reason, the AR order was chosen to remain within the middle of the investigated range at 32. The peak performance for neural networks during this investigatory section was confusion percentages of less than five percent.

5.3 Single Session Performance

In this section we will consider BCIs that are trained with data from a single session and evaluated against both the same data and data from a session not used during training. This distinction is an important consideration from a end-system perspective as it will be shown that a BCI trained from a previous session will not, in this research, perform well from session to session for the same user. This would indicate that a user would be required to train the BCI prior to every use which is undesirable. An ideal system would require one or less training procedures from a user before becoming a functional system independent of when the training took place.

5.3.1 Idle versus Non-idle Mental States

When the BCI system is configured to discern idle versus non-idle mental states, the classifier considers two output classes, and although the same recorded data with all five mental tasks is used, idle is considered one output class and all other states are considered the second class. Essentially, this becomes a classifier with only two mental tasks wherein the data used for the non-idle mental state is more varied since the original four mental tasks are all contributing to train the same neural network output class (as opposed to four separate output classes). The ideal output from Figure 4.1 can be compared visually to the output plot in Figure 5.1 for performance based on the dataset that was used to initially train the BCI. The output of the classifiers is the probability that the input data belongs to the output class. It is clear that the classifier can determine the idle and non-idle periods of ten seconds by the pulses for each task. The TPR and FPR values are listed in Table 5.1. The results for other BCIs that have been individually trained and evaluated against the other data sets are similar to these results.

Table 5.1: Performance Metrics for Single Session Trials

Dataset	**TPR**	**FPR**
Two Task Detection		
In-session	89.02%	3.89%
Out-of-session	18.91%	14.92%
Five Task Detection		
In-session	83.30%	n/a
Out-of-session	21.49%	n/a

However, when a dataset that was not used for training is fed to the BCI system, the performance deteriorates significantly as can be seen by in Figure 5.2 where no clear decision can be made. For comparison, the TPR and FPR are also listed in Table 5.1 under the designation 'Out-of-session'.

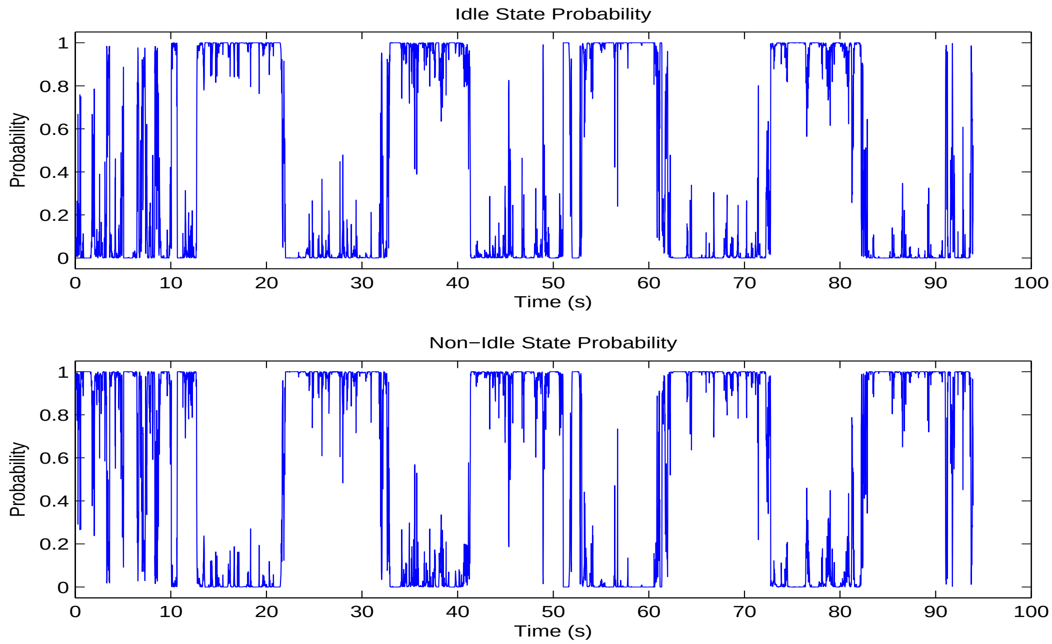

Figure 5.1: Single NN Classifying Two Tasks with In-session Data

5.3.2 Mental Task Detection

When the BCI system is configured to detect all five mental tasks, the output of the voting arbitrator dictates the final output class detected as indicated in Figure 4.4. The voting arbitrator could be a simple maximum value detector utilizing the outputs of the previous neural networks; a more complex implementation may elect to another similar classifier to the ones previously used or a different classifier entirely. In this implementation a simple majority voter is used to select the output classifier reporting the highest probability of its assigned output class. Again, as evidenced in Figure 5.3 and Table 5.1, a BCI performs well with data from which it was trained, and the data from another session fed to the same BCI performs poorly in Figure 5.4

when compared to the ideal output in Figure 4.2. These plots illustrate the positive probability of each individual classifier identifying the input data as belonging to its respective class. In Figure 5.4, it is clear that mental tasks other than idle are unable to identify incoming data. Note that for detecting the five mental tasks as a single BCI system, there is no concept of a FPR, only correct classification and incorrect classification.

5.4 Multiple Session Performance

The poor results for BCIs with data from outside of the initial training is somewhat expected considering the limited scope of the training data and

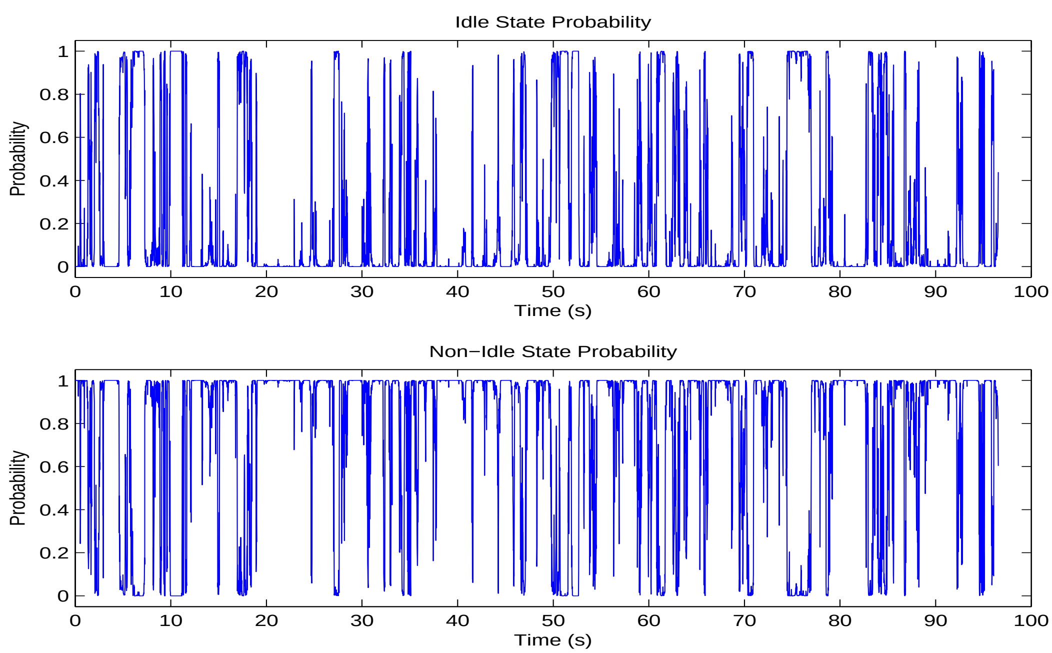

Figure 5.2: Single NN Classifying Two Tasks with Out-of-session Data

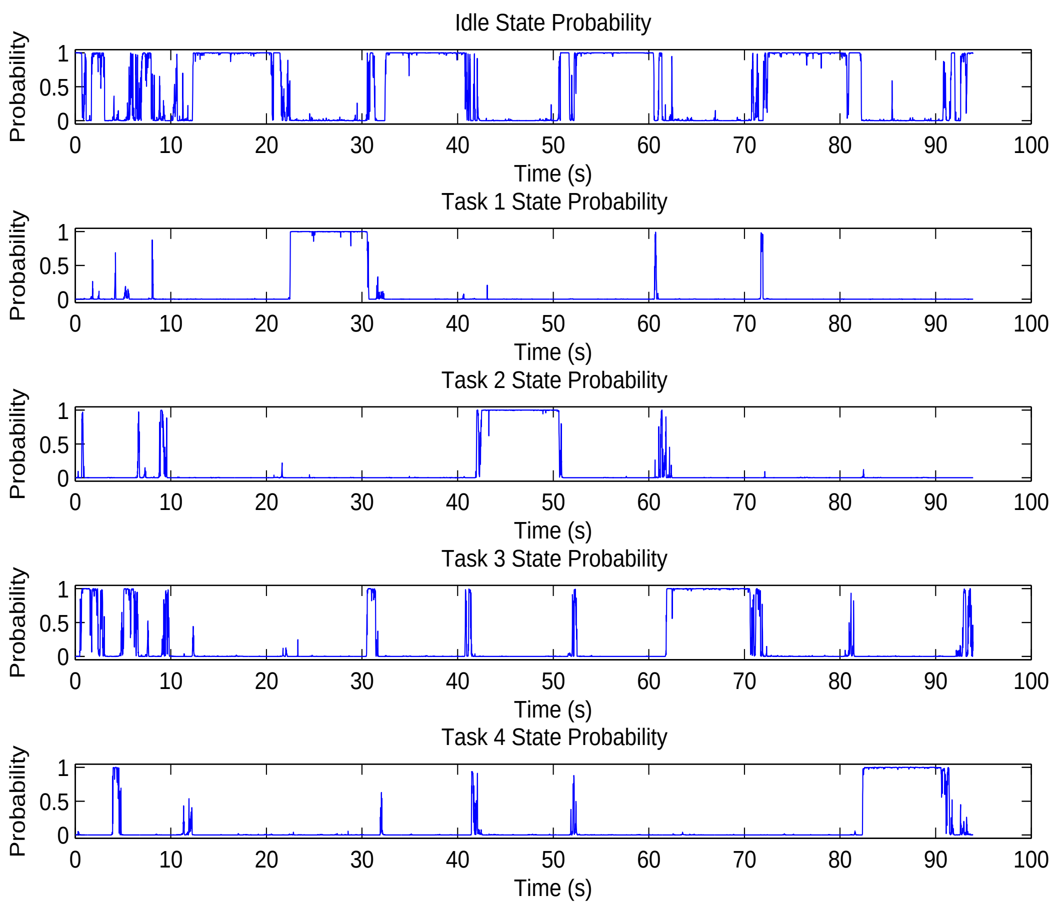

Figure 5.3: Multiple NN Classifying Five Tasks with In-session Data

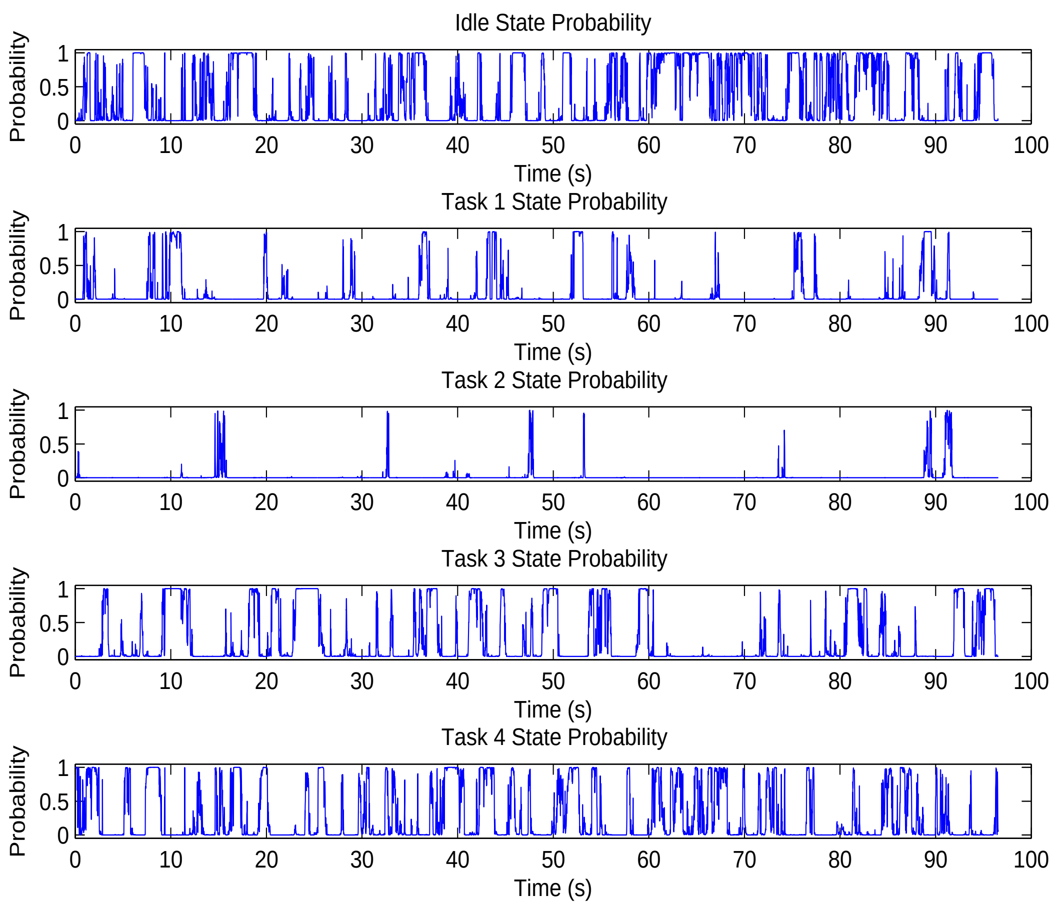

Figure 5.4: Multiple NN Classifying Five Tasks with Out-of-session Data

can be augmented by expanding the training data to include data from all recorded data sets. The following subsections illustrate this effect and the results.

Table 5.2: Performance Metrics for Multiple Session Trials

Dataset	**TPR**	**FPR**
Two Task Detection		
Dataset #1	90.35%	12.34%
Dataset #2	84.73%	13.74%
Dataset #3	87.50%	14.94%
Five Task Detection		
Dataset #1	77.16%	n/a
Dataset #2	73.47%	n/a
Dataset #2	76.54%	n/a

5.4.1 Idle versus Non-idle Mental States

As previously described the same BCI system configured to detect two mental tasks was trained with data from all recorded sessions; the resulting output classification can be seen in Figure 5.5 and performance metrics in Table 5.2. In this case there is no data that is considered 'Out-of-session' as all the data was used to train the network. Although, there are spikes in output probabilty the overall TPR remains approximately the same while FPR increases moderately.

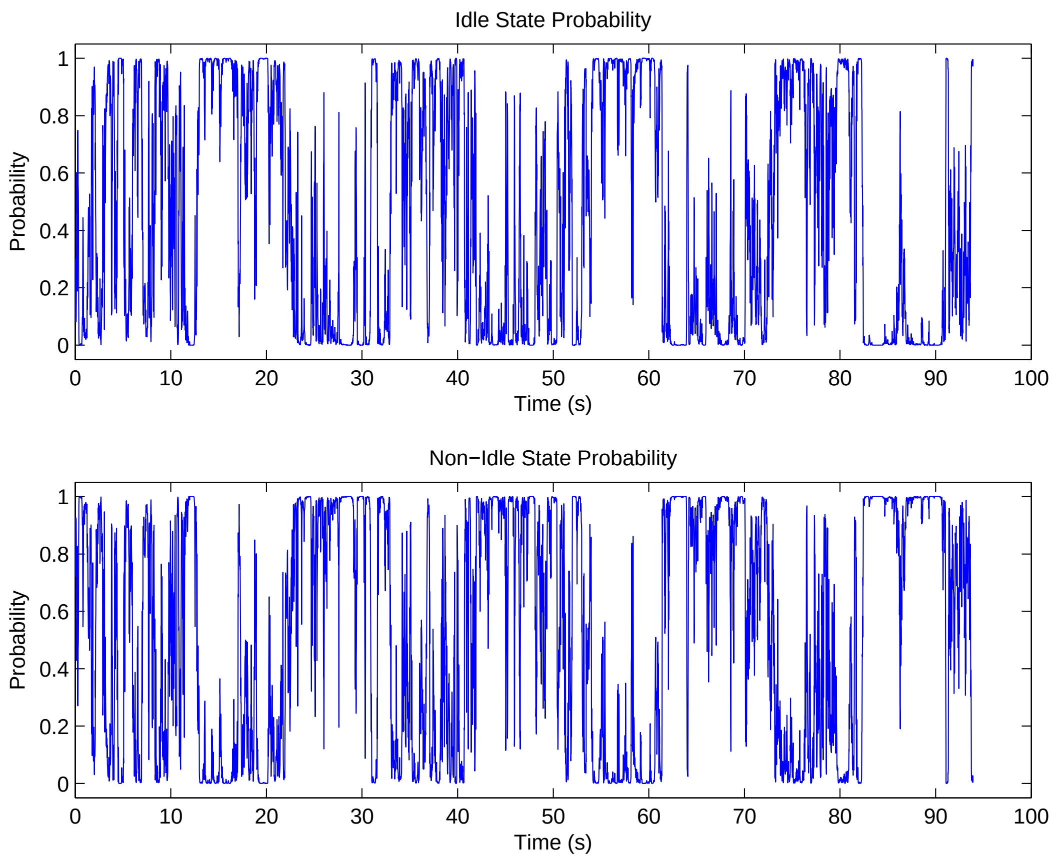

Figure 5.5: Single NN Classifying Two Tasks with Combined Training Data

5.4.2 Mental Task Detection

Finally, the BCI system for all five mental tasks was also trained with data from all recorded sessions. Similarly to the results from the idle versus non-idle, multiple session BCI, these results are an improvement over the out-of-session data results but are inferior to the single-session results. The plot for these results is in Figure 5.6 with the quantitative results in Table 5.2. The distinct pulses for each mental task are prominent with relatively low spurious probabilities.

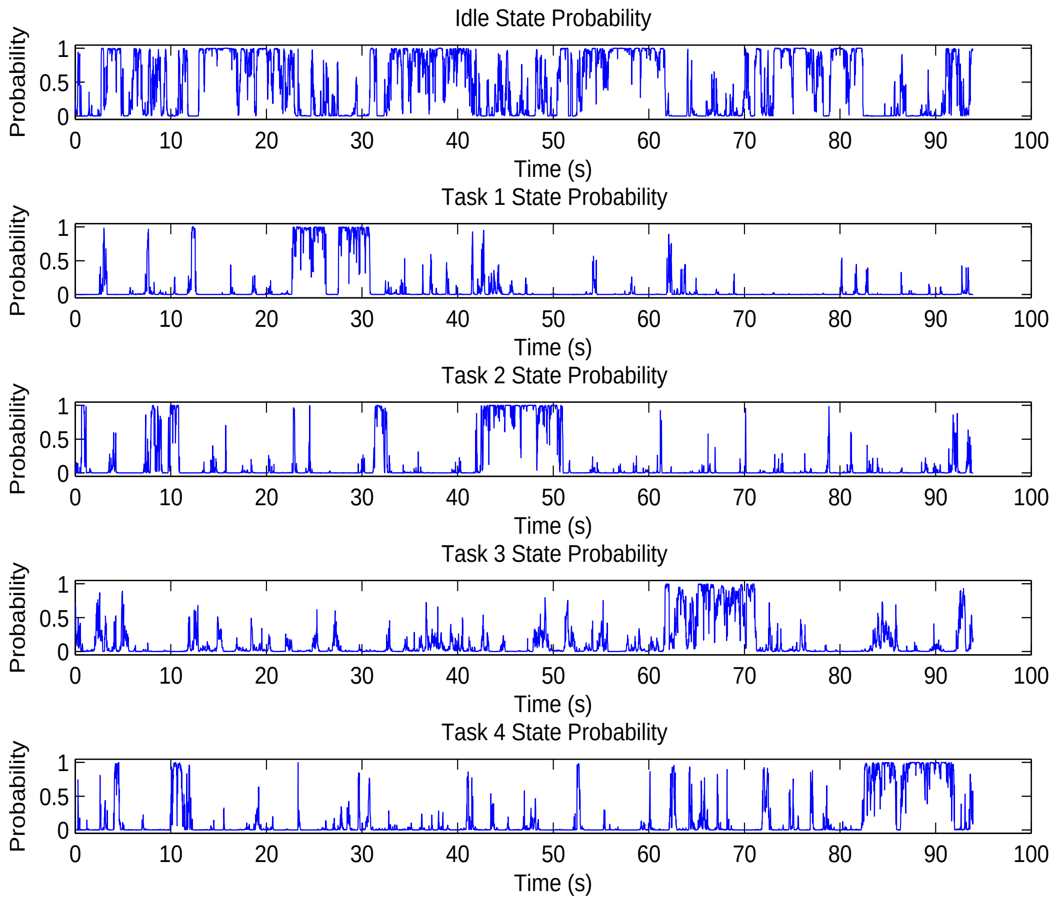

Figure 5.6: Multiple NN Classifying Five Tasks with Combined Training Data

Chapter 6

Conclusions

This research investigated a brain-computer interface system to determine if detecting mental states is possible utilizing a single, dry electroencephalogram sensor. The motivation for this is to develop BCI technology for a convenient, user-friendly human-machine interface. The following sections discuss the results presented in the previous chapter, lessons learned in the course of this investigation, and potential future work to refine the results of this research.

6.1 Discussion of Results

As indicated in the previous chapter, the highest performance occurred for BCIs trained with data from the same session that was tested. Unfortunately, this is a fairly specific test case and not a very good representation of a feasible BCI implementation. This is evident from the non-functional performance of other datasets on the same BCI. The realistic approach to training the neural networks is to use data from multiple sessions in the training providing a wider representation of data for each mental task. This allows the internal nodes of the neural network to recognize the varying features that result from indirect measurement of electrical brain activity. The ability to respond to varying representations is especially limited in this research due to the single sensor implementation used. Research that utilized multiple sensors can use signal-processing algorithms to infer more detail from the collective signal data based on knowledge of the sensor locations and propagation of electrical waves through the cranial fluid and cranium.

In [10], Faradji *et al.* develop a BCI utilizing various combinations of three of the recorded six sensor locations in which 'the FPR reaches zero, while the TPR values are above 71.96%.' While this research does not achieve a zero percent FPR, it does achieve approximately the same or better values for TPR. A notable difference between the two implementations is that Faradji *et al.* focus on minimizing FPR while maintaining high TPR, whereas this research attempts to maximize TPR without regard to the intermediary FPR of the individual classifiers.

Based on these results, it is feasible that single, dry EEG sensor can be used, with moderate reliability, detect mental tasks. The applications of a such a BCI would be dependent on the final TPR and FPR especially for medical related devices.

6.2 Lessons Learned

From the onset of this research the need for a reproducible methodology for data acquisition, processing, and evaluation would be necessary. The developed sequence for subject instruction and data capture proved invaluable for capturing data at different sessions in a consistent manner. Due to the many varieties of features and classifiers, the offline processing took place in a constantly evolving testbench. The use of scripting in MATLAB allowed for these processes to be developed and modified as needed. Additionally, the parameterized functions allowed for rapid testing of preprocessing variables for analysis.

One aspect of researching electrical brain activity through EEG that, although anticipated, still proved to be very difficult was the obscured nature of the actual signals. For all BCI systems, there is no directly measurable indicator of what a subject is thinking. This is different than other quantifiable biological feedbacks such as blood pressure, heart rate, or even DNA where these values can be quantified and test equipment can be proven accurate. Instead, BCIs only rely on what can be observed from the user and effectively utilized with user feedback until a stable configuration is reached and some measure of confidence can be obtained.

While no online processing was performed, if such an implementation were developed, consideration must be given to the hardware/software interaction as a whole. All offline processing during this research was performed on a separate remote system using MATLAB than the initial dataacquisition system, which would complicate online implementations. However, this remote processing may have been unnecessary with the purchase of proprietary software designed for EEG signal processing.

6.3 Future Work

Full realization of a user-friendly EEG BCI still requires additional research in order to come to fruition. While mental task detection was performed adequately in this research, more robust performance would be desirable. One potential area of exploration is the signal capture. This area has two particular aspects that could be investigated: the sensor location and the addition of another sensor. While the forehead is desirable for complete contact with the epidermis, the underlying brain area may provide better results at the cost of SNR due to hair coverage. This trade off has not been investigated extensively. The addition of a second sensor is likely a strong candidate for performance increase. While this would increase the overall system complexity and potentially affect usability, this may provide additional data to support more sophisticated feature extraction.

Another area of exploration to further develop this research would be to reproduce these results with additional test subjects. In order to determine the effectiveness of such a BCI device, multiple test subjects of varied characteristics must be used to eliminate the possibility of non-reproducible results. Since this research focused primarily on a proof-of-concept investigation, only one subject was utilized.

Finally, with a robust developed offline system, the development of an online system detecting mental tasks in real-time would be the next logical step. An online system would be capable of detecting mental tasks as the user performs both known detectable tasks and unknown tasks. Such a BCI would be able to determine unknown tasks as the lack of any detectable task. Ideally, this would be performed as reliably as the ability to detect known tasks.

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Vita

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